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ABSTRACT

Individualized instruction presents problems in measurement which challenge the conventional measurement paradigms. Measurement techniques must take into consideration the problems of item variance characteristics of computer-assisted instruction (CAI), idiosyncratic learning sequences, and lack of a model for effectiveness assessment. The strategies used at the Florida State University CAI Center focus on two major goals: measurement to provide information on priorities for revision within the CAI course materials and measurement to increase the effectiveness of the instructional process. Measurement techniques which are suited to evaluate three levels of course characteristics--microframe, concept segments within a CAI course effectiveness models--are described and foreseeable future trends are briefly discussed. (Author/JY)

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CAI CENTER

TECH MEMO

MEASUREMENT TECHNIQUES FOR INDIVIDUALIZED INSTRUCTION IN CAI

Duncan N. Hansen and Barbara F. Johnson
The Florida State University

Tech Memo No. 35
May 15, 1971

Project NR 154-280
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Duncan N. Hansen and Barbara F. Johnson

I. Introduction

Of the many challenges that individualized instruction poses to conventional measurement paradigms, the most demanding is the performance criterion orientation of computer-assisted instruction. That is, the goal of the CAI program is for all students to reach a specified level of performance through a sequence of objectives or milestones embedded within a training course. This CAI goal plays havoc with the variance characteristics of both the instructional and test response items found within the data records of the individualized course (Hansen, Dick, & Lippert, 1968). A second challenge to conventional measurement is the differential and incomplete learning sequences. These idiosyncratic sequences limit the application of many classical psychometric models and techniques. Still a third CAI challenge is posed by the attempts to assess the total effectiveness of the CAI course; a serious cost-effectiveness assessment would require a utility model which presently does not exist. Even with these many challenges, progress is being made in the creation of new measurement techniques appropriate for the CAI domain.

This paper reviews various measurement techniques used by educational researchers at the CAI Center at Florida State University. The strategy of their approaches to the problems has focused on two

major goals: (a) measurement procedures that yield outcomes that provide insightful information regarding the priorities for revision within the CAI course materials; and (b) measurement outcomes that speak directly to the effectiveness of the instructional process. In order to gain some insight into the pursuit of these two major goals, the measurement techniques can be related to three levels of course characteristics, namely: (a) procedures typically utilized at the CAI microframe level; (b) procedures used for CAI concept segments found within a course; and (c) course effectiveness models which focus on the appropriateness and benefits of CAI course outcomes.

II. Microframe Measurement Techniques

Microframe indices are the dependent measures collected during field tryouts of individualized learning materials, such as mean proportion of correct responses, latency, and subjective confidence. Without a doubt, probability of correct response, or error rate, has been the major item statistic looked at within CAI microframe outcomes. These item statistics present problems for the instructional psychologist in that criterion levels are difficult to defend on either an empirical or theoretical basis. For example, there is little evidence that responding with a 10% or less error rate leads to either superior terminal performance or improved retention. Obviously, wide discrepancies in error rate can result in wide fluctuations in terminal performance; but then, exceedingly high error rates are interpreted as being indicative of inappropriate selection of subjects, or of poorly prepared CAI materials.

Even so, considering incorrect responses, especially in terms of identifying the type and kind of error, provides useful information for the CAI course revision process.

CAI investigations have shown that a baseline plus iterative approach provides meaningful guidelines upon which to base CAI course revision. The primary measurement technique consists of establishing baseline performance via a series of daily or weekly tests administered in a conventional course setting. During the development of an undergraduate physics course (Hansen, Dick, & Lippert, 1968), these investigators administered physics tests according to concept sections to a substantial number of students enrolled in the traditional lecture-demonstration course. This provided a statistical data base for deciding whether the first CAI course was an improvement at the microframe level and for determining which CAI concept areas were most in need of revision. This iterative measurement approach is predicated on the assumption that error rates will be a function of both the type of presentation mode (textbooks, films, programmed instruction, homework problem sets), and the nature of the concepts, especially in a hierarchically organized course.

Table 1 presents the outcome for the first revision of the physics materials. The far right column of the table shows the downward performance trend for students taking the course in a conventional lecture demonstration. For revision, the CAI curriculum developers separated out types of questions associated with different presentation modes, namely, textbooks, films, and conceptual exercises. As can be seen in Table 1, performance on the textbook materials was relatively consistent and undoubtedly a direct function of immediate memory effects typically found

TABLE 1

Mean Correct Proportions on First Responses

to Different Lesson Material Categories

by Physics Topics for First Revision

Concepts	Textbook	Films	Conceptual Exercises	Baseline*
Scientific Measure	.698	.611	.586	.591
Optics and Light	.733	.675	.673	.578
Force and Energy	.706	.547	.666	.483
Electricity	.703	.476	.653	.391
Modern Physics	.703	.486	.695	.412

*Data collected on prior student groups.

in assessing textbook comprehension. On the other hand, it is interesting to note the much wider fluctuation in microframe performance for the film presentations. As to the CAI conceptual exercises, computer-assisted instruction led to superior criterion-level performance indicating that the goal of improved mastery of the more difficult conceptual areas such as found in electricity and modern physics was achieved. From a methodological viewpoint, by summing croframe performance statistics over concepts, a better insight into relative CAI performance and the priorities for revision was gained. This then led to a primary focus on improving the questions associated with the later physics film sections in the course and a secondary focus on providing more CAI conceptual exercises. The iterative revision process resulted in a final course performance of CAI students that was approximately 15% superior on the final exam in comparison with the conventional course students.

An additional measurement revision strategy involves frequent pre- and posttest assessment on clusters of behavioral objectives (Lipe, 1970). Typically, after analyzing difference scores for learning games, investigators rank them in order to identify the behavioral objectives of the course most in need of revision. The rationale for this ranking procedure is that the curriculum developer needs to be parsimonious in his effort and should focus on those behavioral objectives most critically in need of further development. Thus, a rank ordering of pre-posttest difference scores gives an index of the microframes most in need of revision.

Latencies. Latencies on learning and testing materials have been utilized within measurement strategies for CAI. Latencies on study frames (frames presenting the basic conceptual materials) appear to provide the best index of those concepts found most difficult for the students. For a junior high school science course run under CAI (Brown, Conlon, Dasenbrock, Kellogg, Teates, & Redfield, 1970), a substantial inverse relationship appeared between study time and performance on criterion tests. That is, the negative correlation was of the magnitude $r = -.82$. Partialing out the effect of differential lengths of passages still leaves a relatively high correlation, $r = -.62$. From a revision point of view, these latency values provided the basis upon which the basic presentation material was revised within this individualized CAI course. The approach was further substantiated by the finding of a moderate relatioip, $r = .46$, between reading comprehension and terminal course performance for the students in this junior high science CAI course. Thus, the capability for collecting

latencies on CAI presentation frames permits development of a performance index about relative reading or comprehension difficulty which can be combined with the item performance statistics for developing a more refined revision strategy.

Confidence ratings. A recent study concerning a science learning game (Harvey, 1970) indicated that subjective confidence ratings on microframe science concepts yield results parallel to the terminal exam performance, that is, the students' ratings of their confidence in handling questions for specific science concepts were remarkable predictors of their terminal performance. In addition, pre- and posttreatment comparison of the confidence rating on concepts yielded significant positive gains similar to final test performance for the individualized approach which in turn was superior to the conventional lecture discussion condition. Thus, confidence ratings are one more index which can be employed within microframe measurement procedures.

Redundancy identification. An additional microframe technique suggested by Holland (1965) for programmed instruction is that of blocking out materials to identify inefficient redundancies. Random procedures are used to block out sentences with a programmed frame. Similar to the cloze techniques, this procedure produces an index of the impact of specific instructional presentations.

As an equivalent technique, CAI investigators (Brown, Hansen, Thomas, & King, 1970) have composed equivalent materials with differential redundancy levels. The study indicated that allowing students to self-select among redundancy levels leads to effective performance outcomes.

That is, the better performing students consistently choose the more concise presentation and the students with the highest error rates tend to choose the most redundant materials. Though not a direct application of the blockout techniques, this redundancy self-selection procedure does provide performance indices by which to study presentation microframes as opposed to test microframes. Unfortunately, very little empirical work has been performed utilizing these redundancy techniques due to the additional materials preparation requirement.

III. Conceptual Measurement Techniques

The term "conceptual segments" refers to the grouping of concepts to form specified CAI learning sessions. For example, in the CAI physics course, the concepts relating to light would be a CAI concept segment. The basic measurement approach to these larger CAI units has been the attempt to develop quantitative learning models. Extensive effort has been given to developing finite state models and applying them to beginning CAI mathematics problems (Suppes, Jerman, & Bryan, 1968) or sequencing of vocabulary words in initial reading (Atkinson & Wilson, 1969). In essence, the finite state models attempt to define a series of learned and unlearned states and to specify the transition probabilities so as to maintain a record of the current learning state of a student for a given concept. Given the history status, the investigator can decide between the need to continue presenting materials, or the need for review. Unfortunately, the results of experimentation using this type of mathematical model have been far from promising; alternative decision rules appear to lead to inconsequential differences between CAI optimization groups and nonoptimization groups.

Linear regression models. An alternative approach consists of using a linear regression model to keep track of the microframe indices referred to above, an/ dynamically predict terminal performance levels. The measurement techniques within this linear regression approach consist of a two-phased empirical development. First, substantial numbers of students are linearly directed through all the CAI material. As many dependent measures as possible are assessed, and then are regressed against terminal performance levels in order to establish relationships and associated Beta weights. For the second phase, the linear regression model is dynamically employed to predict or identify all failure cause, and CAI remediation is then applied.

In recent experiment performed in the FSU CAI laboratory (Rivers, 1971), this methodology was employed. Initially, 33 students were linearly taken through a CAI program which used scientific concepts for relating heart failure and EKG drawings. Next, the CAI course was segmented into nine concept areas, and the dependent measures of probability of correct response, mean latency on subcriterion items, and trait and state anxiety indices were regressed on terminal performance levels. For each of the nine concepts, a linear regression equation was prepared by which to predict an individual's performance on the terminal test. The experiment was then repeated with four different groups, as follows: (a) a regression optimization group which received remediation and additional practice only if it was predicted that their performance was falling below a preestablished criterion level of 80% on the terminal test; (b) a total remediation control group, that is, a group that received all possible remediation; (c) a student selection group that could self-select remediation

if desired; and (d) a no-remediation control group Table 2 presents the mean final examination performance for these four groups. As can be observed, the optimization group performed better than the other three groups. Moreover, the outcomes were ordered out in a sensibly appropriate fashion; i.e., the total remediation group performed better than the student selection of review materials, or the no-remediation group.

TABLE 2

Mean Final Examination Outcomes for the Optimization Experiment

Groups	Mean	Percentage Correct*
Regression Optimization Group	82.30	65%
Total Remediation Control	77.65	62%
Student Selection	65.45	52%
No Remediation Control	61.45	49%

*Out of 126

Experiments of this type indicate how measurement-based individualization can be extended beyond the concepts of individual learning rates or remedial review conditional on embedded subcriterion tests. In essence, what is gained through a dynmic or continuously updated history record is a more substantial way of predicting performance and intervening with appropriate CAI learning materials. It is worth noting that this technique can be used within computer-managed instruction or programmed

instruction if sufficient automation is applied at various test points via dynamic procedures. These optimization models may hold promise for integrating the performance indices associated with microframe measurement techniques.

IV. Course Assessment

Effectiveness methodology typically compares a lecture demonstration course with some individualized CAI course approach. The most common finding is that those students with lower entry performance levels typically improve significantly more than their counterparts under conventional instruction. For example, Table 3, presenting results from the individualized science learning game (Harvey, 1970), shows that the experimental and conventional control groups, being split at the median, were equivalent on the pretest science achievement measure. Not only did the most significant improvement occur in the lower half of the experimental group, but also this group was substantially superior on a concept specific criterion test that reflected concepts embedded in the individualized materials. As previously mentioned, the subjective confidence ratings improved equivalently with the performance. In addition to this, a short attitude scale indicated significantly positive shifts for the experimental group, a common finding in individualized CAI instruction. Thus, most findings (Majer, 1969; Hagerty, 1970; Lawler, 1971) tend to support the enhanced final performance, positive attitudes, and higher subjective confidence of individualized approaches to instruction.

As the majority of students come to achieve higher levels of mastery via individualization, differential personality factors gain

TABLE 3

Mean Outcomes for Experimental and Control

Groups for the Individualized

Science Learning Game

	Experimental		Conventional Lecture Group	
	Low Entry Group	High Entry Group	Low Entry Group	High Entry Group
General Science Achievement				
Pretest	38.94	52.94	39.06	53.94
Posttest	56.72	59.44	41.78	57.70
Criterion Science Test				
Pretest	25.50	28.22	23.72	29.17
Posttest	43.88	44.33	26.39	31.00
Science Concept Confidence				
Pretreatment	8.78	9.72	9.50	10.67
Posttreatment	11.28	13.28	10.39	11.44
Attitude				
Pretreatment	231.28	281.61	264.28	256.48
Posttreatment	316.17	339.28	292.44	264.17

ascendancy in the instructional process. In the analysis of the CAI physics course, the investigators found that CAI students with a humanistic orientation, low orientation towards science and technology, and high needs for affiliation and trust tended to gain the most from the individualized CAI course (Majer, 1969). In comparison, a subgroup

of students in the conventional lecture session with a personality pattern just the reverse, i.e., theoretically oriented, high values for science, and autonomous tendenceis, was the high performing group. This type of personality investigation, while still in its beginning states, has implications for appropriate selection and assignment procedures within individualized CAI treatments. The need is evident for more research in the affective domain as individualization receives a wider dissemination throughout all levels of education.

Simulation. Simulation techniques for total course assessment can be established to relate course processes and outcomes. In a recent simulation study, King (1970) created a model of an individualized teacher training curriculum, and found that by using the variables of social extroversion (which was negatively correlated ($r = -.70$) with learning time) and cumulative grade point average ($r = .36$ with learning time), the mean learning time could be reduced by 40% by selecting on these cognitive and affective variables. The modeling of an individualized CAI courseng simulation techniques indicated, in King's (1970) study, that it was difficult to shift performance levels due to the high criterion levels observed but that learning time could be manipulated via selection procedures. This simulated finding is highly consistent with empirical findings for individualized courses and illustrates how simulation can aid in course revision and improved effectiveness.

Cost assessment. Individualized instruction systems, especially those utilizing computers, have a higher cost per instructional hour.

Savings in learning time and increases in performance levels are counterbalanced by increased fiscal costs. Utility theory can be employed to related these above factors. Although this is an extremely detailed methodology, the approach can be characterized briefly: one attempts to calculate all potential losses by taking the probability of the risk which is the difference between perfect performance and actual performance and multiply this by the actual cost per instructional hour. These calculations allow for combining outcome performance level with actual instructional costs.

Most recent analyses of this type indicate that the loss coefficients for individualized instruction tend to converge on the costs for conventional courses due to labor factors. Moreover, computer-managed instruction promises to offer an approach that is significantly cheaper with excellent learng outcomes. For example, in a number of courses running at the FSU-CAI Center using CMI (Hagerty, 1970; Lawler, 1971; Dick & Gallagher, 1971), the costs tend to be approximately 60 cents per hour. It should be noted that the computer contact time represents approximately 12% of the course contact involvement. But still, there is a great need for more effectiveness models for relating the current and future outcomes of various individualized approaches so that economical forecasts of their associated costs and outcome potential can be made. Unfortunately, the development of these types of models appears to be exceedingly complex and difficult.

V. Future

In considering future development of measurement techniques for individualized instruction, a number of trends are foreseeable. First,

there is a need for more extensive conventional evaluation, especially dealing with the topics of review and retention. Moreover, it has been recommended that additional incidental measures, beyond at of attitude alone, be considered in evaluating an individualized course. Such factors as attendance, commitment to the importance of the curriculum, and career development are being recommended for consideration. Finally, it is appropriate to recognize the need for models that relate the learning process to personality processes (Leherissey, 1971), since these affective variables become more important in criterion-oriented instruction. Primarily, linear regression models will be employed to perform these investigations, but it is hoped that the use of simulation techniques will become more frequent, since they have a great potential for increased sophistication. The benefit of simulation rests in the identification of the potential application of individualizing procedures such as appropriate selection and assignment of media treatment so as to optimize the potential learning outcomes. Thus, researchers can anticipate that simulation models will become increasingly prominent in attempting to relate the specific empirical outcomes of a given individualized course to its potential application in the broader context of a training system.

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